Int J Life Cycle Assess (2010) 15:272–283
DOI 10.1007/s11367-010-0154-9

LCA FOR FOOD PRODUCTS

# Combined application of life cycle assessment and data envelopment analysis as a methodological approach for the assessment of fisheries

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Received: 6 July 2009 / Accepted: 2 January 2010 / Published online: 9 February 2010


**Abstract**

*Background, aim, and scope* The synergistic use of life cycle assessment (LCA) and data envelopment analysis (DEA) is proposed as a new methodological approach to link environmental and socioeconomic assessments of fisheries. Therefore, the goal is to combine LCA and DEA in order to increase the assessment ability of both tools when applied to these fisheries. Specifically, the joint inclusion of economic aspects and the consideration of currently underrepresented environmental impact categories are tackled.

*Materials and methods* A five-step method is presented to combine LCA and DEA so that operational benchmarking and eco-efficiency verification are included together with the assessment of the environmental performance of fishing vessels. Some guidelines are also provided to orientate methodological choices in DEA. Furthermore, the applicability of the method for fisheries is discussed using a Spanish coastal trawl fishery as an example.

*Results* The use of the five-step LCA+DEA method for fisheries demonstrated the dependence of environmental impacts on the operational performance of the vessels. Operational inefficiencies were detected and target performance improvement values were consequently defined for the inefficient vessels. The combined method favored quantification of potential eco-efficiency gains. Optional features of DEA models allowed the inclusion of controversial impact issues such as by-catch discarding.

*Discussion* As demonstrated by the application of the method to the trawling case study, this methodology facilitates joint consideration of the environmental impacts of the fleet together with economic issues such as operational efficiency. Moreover, the potential inclusion of "bad outputs" in DEA models makes the proposed method suitable for quantifying the potential improvements in currently underrepresented issue areas such as discarding by-catch.

*Conclusions* The proposed methodological approach was found as an adequate alternative to complement the mere use of LCA for fisheries. Its use avoids problems with standard deviations which usually arise when LCA practitioners work with average inventories. Moreover, the new approach facilitates the interpretation of the results for practitioners who deal with multiple individual LCAs for the same fishery. Furthermore, the joint application of LCA and DEA carry synergistic effects related to the link between operational efficiency and environmental impacts.

*Recommendations and perspectives* The proposed LCA+DEA approach for fisheries is recommended for its regular use. The need of multiple input/output data for multiple vessels is not seen as a limitation in the case of fisheries research.

**Keywords** Data envelopment analysis · Discard · Eco-efficiency · Fisheries · Operational efficiency · Seafood · Trawling

## 1 Introduction

In the past few decades, due to a combination of technological developments in fishing technologies, increased fishing effort, and rising demand for seafood

Responsible editor: Niels Jungbluth

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products, there has been a great increase in marine fisheries landings worldwide. Current annual production is in the range of 81.9 million tonnes in 2006 (FAO 2008). However, fishery data suggest a steady decrease in landings mainly due to the overexploitation of the world's major stocks. According to The State of World Fisheries and Aquaculture report of 2008, around 50% of world fisheries are fully exploited, whereas only 25% of them are under-exploited or moderately exploited (SOFIA 2008). Negative trends besetting fisheries must be turned around to promote the rebuilding of supporting ecosystems (Pauly et al. 2003; Worm et al. 2009).

In order to improve fisheries management, efforts must be made to reduce by-catch and discards, the disturbance created in benthic communities due to the use of trawlers and other types of gear, and the alteration of trophic dynamics (Pelletier et al. 2007). Besides these direct impacts caused by fishing activities, research shows that energy demand and materials used in industrial fishing may also create considerable environmental and socioeconomic impacts. These impacts arise from fishing gear usage and loss at sea, anti-fouling agents and paint consumption, ice consumption, and the use of diesel fuel for transportation (Hospido and Tyedmers 2005).

As a result, there is increasing demand for environmental information regarding seafood products by different social groups such as authorities, consumers, companies related to the fishing sector, and skippers (Luten et al. 2006). In an attempt to identify, quantify, and assess environmental impacts throughout the life cycle of seafood, life cycle assessment (LCA) is considered a useful and powerful methodology. Thus, LCA has been proven suitable for quantifying a subset of the environmental impacts associated with fisheries and aquaculture production (Pelletier et al. 2007). However, further efforts are required to improve seafood supply transparency and accountability (Iles 2007; Ayer et al. 2009).

On the other hand, data envelopment analysis (DEA) is a performance measurement methodology used to empirically quantify the comparative productive efficiency of multiple similar entities (Cooper et al. 2007). To carry out a DEA, data for inputs and outputs from the different entities must be known. From these data, DEA formulates and solves an optimization model which facilitates benchmarking the operational performance of each assessed entity. This benchmarking provides a basis for a decrease in inputs per unit of output, usually resulting in improved eco-efficiency. In this sense, DEA enables the discrimination of inefficient operating points, therefore promoting feasible technological improvements under the perspective of an efficient operational performance.

At the same time, whereas many potential environmental impacts of fisheries are not currently accounted for using traditional LCA methodologies (for example, seafloor impacts, discard impacts, ecosystem alteration, etc.), DEA may facilitate consideration of these underrepresented issue areas.

The goal of the present study was to propose a regular methodology to perform a joint analysis of operational efficiency and environmental impacts for fisheries by using the combined application of LCA and DEA. A case study regarding trawling vessels in NW Spain was considered as an example. A complementary goal was to use DEA to simultaneously address currently underrepresented issue areas in LCA research of fisheries; specifically, the discard of by-catch was faced.

## 2 Framework

### 2.1 The problem of multiple inventory data in LCA

Data availability and quality are critical problems in LCA studies (Weidema and Wesnaes 1996; Reap et al. 2008a). LCA practitioners often have to gather inventory data for a high number of similar facilities in order to ensure sample representativeness for a particular case study. Therefore, it is not unusual to handle multiple input/output data. The way multiple data sets are managed may strongly influence the utility of the assessment. A common solution is to establish an average inventory which includes the average values for the different inputs and outputs. However, the high degree of variability often associated with multiple data sets (as evidenced by reported standard deviations) is a barrier. An alternative approach to dealing with multiple inventories is to carry out individual LCAs for each of the inventories. This approach may better represent variability, but the multiple results may be difficult to interpret.

In such situations, a promising alternative which simultaneously (1) avoids large standard deviations, (2) facilitates the interpretation of the results, and (3) provides useful additional information to complement LCA with a non-parametric tool called DEA is introduced in Section 2.2. This approach is clearly relevant for LCA research of fisheries due to the need to assess many fishing vessels to guarantee representativeness.

### 2.2 An introduction to DEA

DEA (Cooper et al. 2007) is a linear programming method to measure the efficiency of multiple decision-making units (DMUs) when the production process involves multiple inputs and outputs. A DMU is defined as the entity responsible for the conversion of inputs into outputs and whose performance is the object of assessment. DEA non-parametrically estimates the relative efficiency of a number

of DMUs. Therefore, DEA neither requires the user to set weights for each input and output nor demands the establishment of any functional form. Rather, DEA simply relies on the observed data for the inputs and outputs and on a minimum of basic assumptions to solve an optimization model formulated for every DMU. DEA estimates production efficient frontiers for a number of homogenous units (DMUs); in mathematical terms, these efficient frontiers are said to envelop all units. The region determined by the efficient frontiers is called production possibility set (PPS), and the DMUs on the frontiers constitute the reference set. The result for each DMU is an efficiency score and, for those DMU identified as inefficient, a target operating point.

The stand-alone use of DEA has already been proposed for environmental performance analysis and for eco-efficiency assessments (Kuosmanen and Kortelainen 2005, 2007; Kortelainen 2008). However, if life cycle inventory (LCI) data are available, it is possible to synergistically link the use of LCA and DEA in order to more effectively detect and remedy the technical inefficiencies that are sources of unnecessary environmental impact (Lozano et al. 2009).

### 2.3 Specific framework for fisheries

When performing an LCA for fisheries, an accurate study requires the assessment of a representative number of vessels. From a DEA perspective, each vessel represents a DMU. The rule of thumb to determine the minimum sample size in DEA is: $n \geq \max\ \{m \times s, 3 \times (m + s)\}$ (Cooper et al. 2007), where $m$ is the number of inputs used in the DEA study and $s$ is the number of outputs involved. For example, the simplest case for DEA would just consider one input (diesel consumption) and one output (catch rate), so at least six vessels should be studied. However, the number of inputs and outputs of interest for a DEA study on fisheries is expected to be much higher. Nevertheless, this fact is not a problem for fishery case studies since the number of vessels which guarantees sample representativeness must be high enough to allow LCA practitioners to include DEA in their case study. Consequently, the LCA+DEA method proposed in this section will generally prove feasible in fisheries LCA research and can be understood as a regular procedure for fisheries.

## 3 Proposed methodology

This paper develops how LCA and DEA should be jointly applied for the study of the environmental and economic performance of fisheries. The recommendation is that LCA practitioners use the most relevant LCI data in order to carry out a complementary DEA study. This will lead to virtual feasible targets that will be object of further treatment by using LCA to check and quantify eco-efficiency. In this section, a guide to the steps to be undertaken is presented together with some guidelines to perform a DEA. Finally, this section highlights the benefits of using this extended method for LCA. These benefits refer mainly to the inclusion of issues for which well-established impact assessment methods have not been developed (Pelletier et al. 2007), such as the consideration of by-catch and discards in fisheries (Ziegler et al. 2003; Ziegler and Valentinsson 2008).

### 3.1 LCA+DEA steps

As summarized in Fig. 1, the proposed LCA+DEA methodology for fisheries comprises five main steps:

1. LCI for each of the DMUs (vessels). In this stage, input and output data for the assessed system are collected.
2. Life cycle impact assessment for every vessel from the LCI developed in the first step. This second stage constitutes the environmental characterization of the current vessels' performance.
3. DEA from the LCIs of the first step: Determination of the operational efficiency of each DMU and calculation of the target DMUs. The use of DEA on the most relevant input/output data leads to computing the relative efficiency of each vessel and setting appropri-

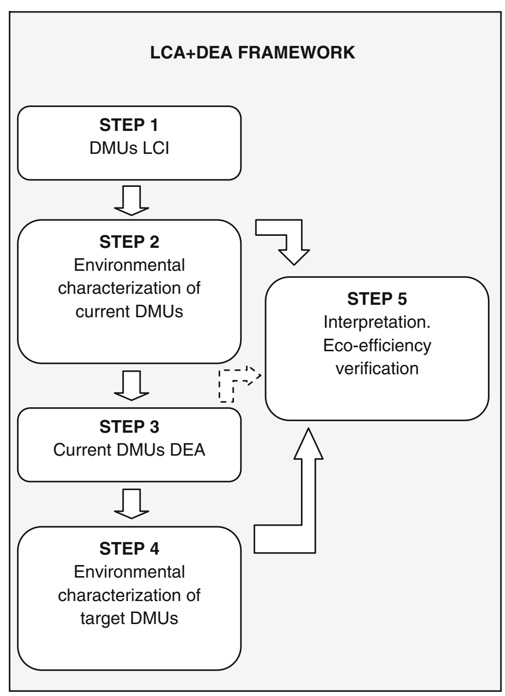


**Fig. 1** Schematic representation of the LCA+DEA methodology for fisheries

ate efficiency targets. The DEA targets represent virtual vessels which consume less input and/or produce more output. These targets are calculated by projecting each DMU on the efficient frontier determined by the reference set. Note that each DMU has its own reference set, so this step should not be misunderstood as a simple calculation of a distance-to-target for the less efficient vessels through a simple scan of the inventory data sets. Therefore, at this point, the performance of multiple vessels is benchmarked from an economic/operational perspective.

4. Environmental characterization of the target vessels. In this fourth stage, the potential environmental impacts are determined for the virtual DMUs by performing a life cycle impact assessment with the new LCI data arising from the previous step.
5. Comparison of the potential environmental impacts for the virtual vessels versus those for the current vessels. This step shows how environmental impacts depend on the efficiency with which operations are carried out. Links between operational efficiency and environmental impacts are then established and the environmental consequences of operational inefficiencies can be estimated.

An alternative approach would consist of only three stages. The first two steps would be the same as those described above. However, the third stage would comprise a DEA with a higher number of inputs given the consideration of the potential environmental impacts determined in the second step as inputs for the DEA along with the selected LCI inputs (Lozano et al. 2010). In this sense, the benchmarking results would directly estimate targets for both LCI inputs/outputs and the potential environmental impacts. For LCA practitioners, this alternative is considered as less interesting than the previous one since DEA itself is not a method conceived for environmental management but for operational (economic) management. Therefore, the recommendation is to benchmark the operational performance of the vessels and then carry out an LCA with the new target LCI. Moreover, according to the rule of thumb for sample size, the second approach would result in an increased number of DMUs to be assessed so as to guarantee an adequate number of degrees of freedom for the efficiency discrimination among DMUs in DEA; this is due to the higher number of inputs ($m$). Note that if $n < m + s$, then a large portion of the DMUs will be deemed efficient, and efficiency discrimination turns disputable.

### 3.2 Recommendations to perform DEA

A wide range of models to perform DEA are available (Zhu 2002). Three factors have to be taken into account when selecting a model (Lozano et al. 2009): (1) metric (radial or non-radial), (2) orientation (toward inputs, toward outputs, or mixed orientation), and (3) PPS display. This third factor merits further attention. In this sense, even though DEA does not rely on assumptions that the data come from any specific production function, some assumptions are usually made to perform DEA. The three common assumptions are convexity, scalability, and free disposability of inputs and outputs. When the three assumptions are made, the PPS is said to display constant returns to scale (CRS). On the other hand, if convexity and free disposability but not scalability are assumed, then the PPS displays variable returns to scale (VRS).

A model which meets the features required by the user should be selected. It can be difficult to choose between CRS and VRS. The general recommendation is to assume VRS where the user suspects that not all the DMUs operate at an optimal scale (Banker 1984). To simplify model selection in the general LCA+DEA methodology for fisheries, a review of the methodological choices for the attempts made to date when using LCA and DEA for fisheries and extensive aquaculture can be useful.

Lozano et al. (2009) carried out a joint application of LCA and DEA for mussel aquaculture by adopting a five-step LCA+DEA approach; the DEA model used was the enhanced Russell graph measure model. Model features included mixed orientation, non-radial metric, and CRS. On the other hand, in (Lozano et al. 2010), a three-step approach is proposed for the combined application of LCA and DEA also in mussel aquaculture with the same model features, but resorting to the slacks-based measure (SBM) model.

Current studies of the LCA+DEA method for fisheries include the assessment of the Galician (NW Spain) coastal trawlers, coastal purse seiners, and Grand Sole long liners. In all these cases, a five-step LCA+DEA method was preferred as well as a non-radial metric and CRS. For coastal purse seining and Grand Sole long-lining, an input-oriented SBM model was selected, whereas for coastal trawling, a non-oriented slacks-based measure with undesirable outputs (SBM-Undesirable) model was chosen.

According to these case studies, a common trend toward the use of CRS and non-radial DEA models is observed. Furthermore, the preferred approach was the five-step LCA+DEA method for fisheries.

It is important to highlight that DEA models are already implemented in software tools such as DEA-solver Pro (Saitech 2009), an Excel-based program designed on the basis of Cooper et al. (2007).

### 3.3 Advantages of the LCA+DEA method

LCA for fisheries presents a number of challenges. Some of them are related to LCA itself, such as the current lack of

accepted methodologies to assess the social and economic dimensions of product or service systems. Other challenges arise in accounting for fishery-specific impacts, such as benthic disturbance due to bottom trawling or the biodiversity impacts caused by discards and by-catch. Some methodological development efforts have to be made in these areas (Pelletier et al. 2007). The LCA+DEA method may also contribute to partly resolving these challenges, for example by providing an economic perspective or benchmarking the discard levels.

LCA is traditionally focused only on environmental impacts. In fact, ISO documentation limits LCA's purview to environmental effects (ISO 2006a, 2006b). From a sustainable development perspective, this may limit the capability of LCA to support decisions (Reap et al. 2008b). In this sense, the LCA+DEA methodology adds an economic dimension to the assessment by evaluating the operational performance of the vessels. Therefore, complementary use of DEA provides LCA with a stronger potential to support decision making because it facilitates benchmarking both the environmental and the operational performance of the assessed vessels.

Eco-efficiency is based on creating more goods and services while using fewer resources and creating less waste and pollution. The term eco-efficiency was coined by the World Business Council for Sustainable Development to demand the delivery of competitively priced goods and services that satisfy human needs and bring quality of life while progressively reducing environmental impacts of goods and resource intensity throughout the entire life cycle to a level at least in line with the Earth's estimated carrying capacity (Schmidheiny 1992). The joint application of DEA and LCA allows the benchmarking of the environmental and operational performance of vessels, which provides a basis for targeting effective means of reducing environmental impacts if the determined operational targets are achieved. The proposed LCA+DEA method for fisheries is in accordance with the eco-efficiency concept and arises as a simple approach geared toward sustainability and not limited to environmental impacts.

Application of DEA models gives rise to other advantages related to the specific model chosen by the user. For instance, weighted models enable users to assign weights to inputs and outputs corresponding to the relative importance of items; for example, instead of giving the same priority to every input reduction, the reductions in each of the inputs can be differently weighed by giving more priority to the reduction of those inputs that contribute more to the environmental impact categories (Thanassoulis and Dyson 1992).

DEA models can also be used to address certain issue areas for which accepted impact assessment methods have not been developed. For example, DEA OBad models, which minimize "bad outputs" from product or service systems, might be used to account for discards from fisheries. DEA usually assumes that producing more outputs relative to less input resources is a criterion of efficiency. However, this clearly does not apply to undesirable outputs, such as polluting emissions or wasted resources. In the presence of undesirable outputs, technologies with better (desirable) outputs and less undesirable outputs relative to less input resources should be recognized as efficient (Cooper et al. 2007). LCA+DEA method for fisheries can employ an OBad model to integrate discarding in the assessment by benchmarking its values on the basis of real discard LCI data (i.e., minimizing discard values from a DEA perspective) rather than by implementing a new impact category from an LCA perspective.

The LCA+DEA approach has previously been successfully applied to the evaluation of extensive aquaculture production (Lozano et al. 2009). Moreover, in the next section, the potentials of the new methodological approach for fisheries are shown and discussed on the basis of a specific case study.

## 4 Application of the proposed LCA+DEA method to coastal trawling

As previously described, a joint LCA and DEA approach can be implemented to assess the operational efficiency and environmental impacts of fisheries. The fact that the extraction phase of most fisheries typically involves a great number of vessels makes this methodology useful and applicable to nearly every fishery in the world.

### 4.1 Case study

The example proposed is an LCA of a sample of trawling vessels belonging to the Galician fishing ground. The study aimed at quantifying the environmental impact associated with the landing of various fish species caught by Galician trawling vessels on the Galician continental shelf during 2008. The main tradable species that are sold by Galician trawlers are European hake (*Merluccius merluccius*), horse mackerel (*Trachurus trachurus*), Atlantic mackerel (*Scomber scombrus),* and blue whiting (*Micromesistius potassou*). Hake was sold that year at 3.72€/kg, being the most expensive of these species at the fish market. All the other species had a similar value at the fish market ranging from 0.89€/kg for blue whiting to 0.51€/kg for Atlantic mackerel (Xunta de Galicia 2008).

The functional unit (FU) considered was 1 kg of landed fish. The rationale behind this FU choice, rather than adopting a product perspective, is its ability to analyze the operational and environmental performance of the different vessels. In other words, an FU referred to only one specific

product would prevent the assessment from getting a realistic perception of the vessels' performance. The system under study comprised the different stages considered for fish extraction performed by the different vessels in the fishery, including diesel consumption, anti-fouling, oil and trawl nets use, and ice consumption. The construction and maintenance of the vessels was also included. The product was followed from the fishery until landing for sale, constituting a "cradle to gate" analysis (Guinée et al. 2001).

### 4.2 Data acquisition

The sample used for the case study is a group of 24 trawling vessels belonging to the Galician fishing fleet. These vessels represent 24% of the total Galician continental shelf trawling fleet (Xunta de Galicia 2008). The data were obtained through a series of questionnaires filled out by skippers from three of the most important trawling ports in Galicia (Celeiro, Muros, and Ribeira). Questionnaires comprised a wide range of operational aspects (annual consumption of diesel, oil, and antifouling paint; ice consumption or trawl net consumption) as well as aspects related to capital goods (hull material, vessel dimensions, useful life, etc.). Background process data were derived from the ecoinvent database (Frischknecht et al. 2007).

The input and output data for the DEA of the 24 DMUs are shown in Table 1 and correspond to the most important primary data from the questionnaires. A total of six inputs and two outputs were considered, all of which related to the vessels main activities. Therefore, the rule of thumb for minimum sample size is satisfied (24 vessels required). It is important to point out that the emissions to air due to diesel combustion or emissions to seawater from anti-fouling agents were not considered in the table, owing to their direct proportion with respect to the amounts of diesel and anti-fouling consumed. Consequently, by minimizing these inputs, at the same time, we are minimizing the direct emissions from the DMUs. The outputs considered were the discarded fish and the catch value of each vessel. Global catch value for all the species was chosen as an output instead of their individual catch rates for two main reasons. Firstly, the species captured by the different vessels were not uniform. Therefore, the catch value was included as the output in an attempt to standardize all the captures of the Galician coastal trawling fleet. Secondly, including the separate catch rates of the different species would increase the good outputs to four, so a larger sample of vessels would be needed to carry out the DEA. It should also be noted that the discarded fish (a mixture of commercial and non-commercial species) is referred to as a "bad output" due to its undesirable character. At first, selecting the global catch value as the output for DEA could seem inconsistent with the FU previously defined for LCA; however, the output reference for DEA must observe the economic nature of this tool. In this sense, a global catch rate would distort the real purpose of the benchmarking pursued by fishers, which is not to fish more but to earn more. Given the difference in the value of the species, an increase in fish captures does not guarantee a greater turnover. Furthermore, in this case study, the choice of the global catch value does not entail problems when transferring the target percentage reductions of the inputs and bad outputs to the LCI data for the environmental characterization of the target vessels; this is due to the invariance of the target outputs related to the original ones, then maintaining the same catch rate distribution.

### 4.3 Justification of the case study

The implementation of DEA in LCA studies is a useful methodology in situations with a large range of data characterized by significant standard deviations. In these cases, an average inventory does not provide a realistic assessment of the operational and environmental performance of the inventoried facilities. For the proposed case study, the standard deviation for the main inputs and outputs was evaluated in order to determine the appropriateness of using an average inventory. Table 2 presents the data obtained for this study.

As shown in Table 2, high standard deviations were observed for all inputs and outputs, ranging from 27% (diesel consumption) to 68% (discarded fish). These values recommend against the use of average inventory data set which would mask the considerable variability in operational and environmental performance within the fleet. Other alternatives to face high standard deviations include the modeling of representative and coherent facility types based on accountancy data for use in environmental assessments (Dalgaard et al. 2004, 2006). In this sense, within each facility type, there must be a consistent relation between resource use, production, and emissions.

Although Table 2 reflects a specific situation, high standard deviations are expected to be a common characteristic when fisheries are inventoried. The reasons behind this relevant variability include the migratory nature of most species, the lack of a standard operation of the different vessels (Schau et al. 2009), the variable characteristics of these vessels, and even the skipper skill (Ruttan and Tyedmers 2007).

### 4.4 Methodology application

#### Step 1: DMUs LCI

The first step of the methodology is to obtain all the data that need to be included in the LCI. It is also important to have

**Table 1** Input and output data for DEA

| DMU | O Catch value (€/year) | OBad discards (kg/year) | I-1 Diesel (l/year) | I-2 Lubricating oil (l/year) | I-3 Paint (l/year) | I-4 Trawl net (kg/year) | I-5 Steel for boat construction (kg/year) | I-6 Ice (kg/year) |
|---|---|---|---|---|---|---|---|---|
| 1 | 443,996 | 868,600 | 404,000 | 1,650 | 408 | 2,059 | 3,933 | 237,350 |
| 2 | 718,655 | 849,915 | 404,000 | 1,200 | 362 | 1,416 | 3,074 | 230,000 |
| 3 | 718,655 | 849,915 | 404,000 | 1,316 | 261 | 1,416 | 2,416 | 220,000 |
| 4 | 917,952 | 1,167,508 | 440,000 | 1,600 | 460 | 1,294 | 4,333 | 180,000 |
| 5 | 917,952 | 444,766 | 480,000 | 1,600 | 460 | 1,294 | 4,333 | 172,000 |
| 6 | 796,224 | 981,888 | 404,000 | 1,200 | 527 | 1,416 | 4,840 | 161,600 |
| 7 | 1,214,898 | 605,025 | 350,000 | 1,350 | 509 | 1,392 | 4,707 | 200,160 |
| 8 | 1,214,898 | 605,025 | 347,000 | 1,300 | 401 | 1,392 | 3,330 | 198,000 |
| 9 | 521,226 | 326,203 | 404,000 | 1,250 | 289 | 1,392 | 3,032 | 215,000 |
| 10 | 521,226 | 326,203 | 404,000 | 1,450 | 460 | 1,392 | 3,712 | 202,000 |
| 11 | 808,032 | 244,273 | 500,000 | 1,650 | 390 | 1,877 | 3,800 | 343,400 |
| 12 | 554,040 | 206,353 | 480,000 | 2,400 | 390 | 2,333 | 4,560 | 202,000 |
| 13 | 1,466,566 | 472,208 | 440,000 | 2,750 | 390 | 1,877 | 3,800 | 363,600 |
| 14 | 701,036 | 395,074 | 396,000 | 2,400 | 390 | 2,150 | 3,257 | 222,200 |
| 15 | 1,005,718 | 747,434 | 330,000 | 1,800 | 256 | 1,051 | 2,781 | 171,700 |
| 16 | 1,005,718 | 215,173 | 355,000 | 1,800 | 299 | 1,051 | 2,390 | 171,700 |
| 17 | 1,326,989 | 199,770 | 292,900 | 1,496 | 390 | 1,051 | 3,257 | 202,000 |
| 18 | 1,326,989 | 431,775 | 305,000 | 1,316 | 190 | 1,051 | 1,827 | 202,000 |
| 19 | 1,353,235 | 781,943 | 383,800 | 4,000 | 231 | 2,796 | 2,222 | 202,000 |
| 20 | 575,377 | 272,575 | 242,400 | 600 | 387 | 2,024 | 3,234 | 212,100 |
| 21 | 575,377 | 272,575 | 250,400 | 1,300 | 387 | 2,024 | 3,773 | 212,100 |
| 22 | 660,298 | 315,060 | 303,000 | 800 | 355 | 1,416 | 3,029 | 202,000 |
| 23 | 928,290 | 37,870 | 378,750 | 600 | 321 | 1,173 | 2,809 | 303,000 |
| 24 | 565,931 | 75,098 | 242,400 | 1,800 | 355 | 1,568 | 3,029 | 161,600 |
| Total | 20,839,278 | 11,692,229 | 8,940,650 | 38,628 | 8,868 | 37,906 | 81,479 | 5,187,510 |

the DEA matrix well defined with the selected inputs and outputs, making sure that they meet the rule of thumb for sample size.

Step 2: Environmental characterization of current DMUs

Once the LCI stage is complete, individual LCAs for each of the vessels are carried out. The specific software used for the computational implementation of the LCIs was SimaPro 7 (Goedkoop et al. 2008) using CML baseline 2000 as the environmental impact assessment method. In this particular study, six impact categories were taken into account, excluding the toxicity and ecotoxicity impact categories due to the uncertainties in the results (Ziegler and Valentinsson 2008). The impact categories included were abiotic depletion potential (ADP), global warming potential (GWP), photochemical oxidant formation potential (POFP), eutrophication potential (EP), acidification potential (AP), and ozone layer depletion potential (ODP). It must be noted that this case study is only an example for the application of the proposed LCA+DEA method; therefore, other environmental impact assessment methods could be equally applied if judged more convenient. For example, given the importance of fuel use, the application of the cumulative energy demand method (VDI-Richtlinien 1997) might be also interesting in order to add cumulative energy demand as another impact category.

This second step of the LCA+DEA method is here performed by adopting an attributional (retrospective) LCA; however, the later target values from step 3 could be useful for future change-oriented (prospective or consequential) assessments (Ekvall et al. 2005).

Step 3: Current DMUs DEA

The following step is to calculate the efficiency scores of the different DMUs in the DEA program. The software used to implement this model was DEA-Solver Professional Release 6.0 (Saitech 2009) using in this case an SBM-Undesirable Outputs model. The rationale of this model is the inclusion of a so-called bad output in order to take into account the discarded fish in

**Table 2** Determination of the standard deviations for the main data of the Galician coastal trawling

| DMU | OBad (kg/FU) | I-1 (l/FU) | I-2 (l/FU) | I-3 (l/FU) | I-4 (kg/FU) | I-5 (kg/FU) | I-6 (kg/FU) |
|---|---|---|---|---|---|---|---|
| 1 | 2 | 0.93 | 0.0038 | 0.00094 | 0.0047 | 0.0091 | 0.55 |
| 2 | 1.5 | 0.71 | 0.0021 | 0.00064 | 0.0025 | 0.0054 | 0.41 |
| 3 | 1.5 | 0.71 | 0.0023 | 0.00046 | 0.0025 | 0.0043 | 0.39 |
| 4 | 1.49 | 0.57 | 0.0021 | 0.00059 | 0.0017 | 0.0056 | 0.23 |
| 5 | 0.57 | 0.62 | 0.0021 | 0.00059 | 0.0017 | 0.0056 | 0.22 |
| 6 | 1.52 | 0.62 | 0.0018 | 0.00080 | 0.0022 | 0.0074 | 0.25 |
| 7 | 0.67 | 0.39 | 0.0015 | 0.00056 | 0.0015 | 0.0052 | 0.22 |
| 8 | 0.67 | 0.38 | 0.0014 | 0.00044 | 0.0015 | 0.0037 | 0.22 |
| 9 | 0.67 | 0.83 | 0.0026 | 0.00059 | 0.0028 | 0.0062 | 0.44 |
| 10 | 0.67 | 0.83 | 0.0030 | 0.00094 | 0.0028 | 0.0076 | 0.41 |
| 11 | 0.29 | 0.60 | 0.0020 | 0.00047 | 0.0022 | 0.0046 | 0.41 |
| 12 | 0.23 | 0.55 | 0.0027 | 0.00044 | 0.0027 | 0.0052 | 0.23 |
| 13 | 0.35 | 0.33 | 0.0021 | 0.00029 | 0.0014 | 0.0029 | 0.27 |
| 14 | 0.42 | 0.42 | 0.0026 | 0.00042 | 0.0023 | 0.0035 | 0.24 |
| 15 | 1.71 | 0.76 | 0.0041 | 0.00059 | 0.0024 | 0.0064 | 0.39 |
| 16 | 0.49 | 0.81 | 0.0041 | 0.00069 | 0.0024 | 0.0055 | 0.39 |
| 17 | 0.35 | 0.51 | 0.0026 | 0.00068 | 0.0018 | 0.0057 | 0.35 |
| 18 | 0.75 | 0.53 | 0.0023 | 0.00033 | 0.0018 | 0.0032 | 0.35 |
| 19 | 0.57 | 0.28 | 0.0029 | 0.00017 | 0.0020 | 0.0016 | 0.15 |
| 20 | 0.83 | 0.74 | 0.0018 | 0.00012 | 0.0062 | 0.0099 | 0.65 |
| 21 | 0.83 | 0.77 | 0.0040 | 0.00012 | 0.0062 | 0.0115 | 0.65 |
| 22 | 0.75 | 0.72 | 0.0019 | 0.00084 | 0.0034 | 0.0072 | 0.48 |
| 23 | 0.06 | 0.55 | 0.0009 | 0.00047 | 0.0017 | 0.0041 | 0.44 |
| 24 | 0.22 | 0.70 | 0.0052 | 0.00010 | 0.0045 | 0.0087 | 0.46 |
| Mean ± SD | 0.80±0.54 | 0.62±0.17 | 0.0026±0.0010 | 0.00064±0.00027 | 0.0027±0.0014 | 0.0058±0.0024 | 0.37±0.14 |

the system. The model demands the inclusion of two additional numbers: the total weight assigned to good outputs and the total weight assigned to bad outputs. In this case, no weighting was considered necessary, so the default 1 and 1 values were introduced in the program. The DEA model was then used to identify the efficient and the non-efficient DMUs and to formulate a new virtual and efficient value for the different inputs and outputs of the inefficient DMUs by projecting the inefficient values on the efficient frontiers established by the efficient DMUs (i.e., by the reference set, which can be different for each of the vessels). Obviously, efficient DMUs did not experiment any changes, with their corresponding target coinciding with their actual operating point. Table 3 shows the efficiency scores computed with the SBM-Undesirable outputs model. As observed, only four of the 24 vessels were deemed efficient (i.e., efficiency score of 100%). This allowed important input target reductions (larger than 60% in some cases) which are expected to entail significant reductions in environmental impacts. Note that efficient vessels do not involve identical performances since, in this context, efficiency only means that according to the real data observed and the three basic assumptions (convexity, scalability, and free disposability of inputs and outputs), it is not possible to produce more without increasing resource consumption.

**Table 3** Efficiency scores ($\Phi_0$) for the 24 vessels according to the SBM-Undesirable outputs model for DEA

| DMU | $\Phi_0$ (%) | DMU | $\Phi_0$ (%) |
|---|---|---|---|
| 1 | 15.13 | 13 | 60.29 |
| 2 | 30.42 | 14 | 27.36 |
| 3 | 32.46 | 15 | 51.57 |
| 4 | 36.00 | 16 | 72.31 |
| 5 | 42.38 | 17 | 100.00 |
| 6 | 33.50 | 18 | 100.00 |
| 7 | 56.86 | 19 | 100.00 |
| 8 | 60.98 | 20 | 37.36 |
| 9 | 25.14 | 21 | 29.23 |
| 10 | 22.82 | 22 | 39.59 |
| 11 | 36.49 | 23 | 100.00 |
| 12 | 23.05 | 24 | 47.00 |

Step 4: Environmental characterization of target DMUs

Once the target values obtained in the DEA model for the inefficient trawling vessels are available, they underwent a new environmental impact assessment through LCA in order to calculate the impacts of these vessels if they are operated in an efficient way. Once again, note that target vessels usually show a different environmental performance because of the differences in their target input (and undesirable output) inventories, even though they are all deemed efficient. This second environmental characterization should not be understood as a pure consequential LCA (Ekvall et al. 2005) but as a descriptive assessment of the current vessels if they are operated at an optimized scale.

Step 5: Interpretation and eco-efficiency verification

Finally, as seen in Fig. 2, the environmental impacts per kilogram of output (i.e., per FU) of the original DMUs were compared to those associated with their virtual targets. Usually, the environmental impacts in the virtual targets were lower than the ones of the original DMUs due to the optimization of the resources.

On the other hand, for the fleet as a whole, Fig. 3 represents how the total target environmental impact was considerably lower than the current one for all the impact categories. The categories that benefited the most from operational optimization were ODP and ADP (around 44% improvement). At the same time, Fig. 3 also shows

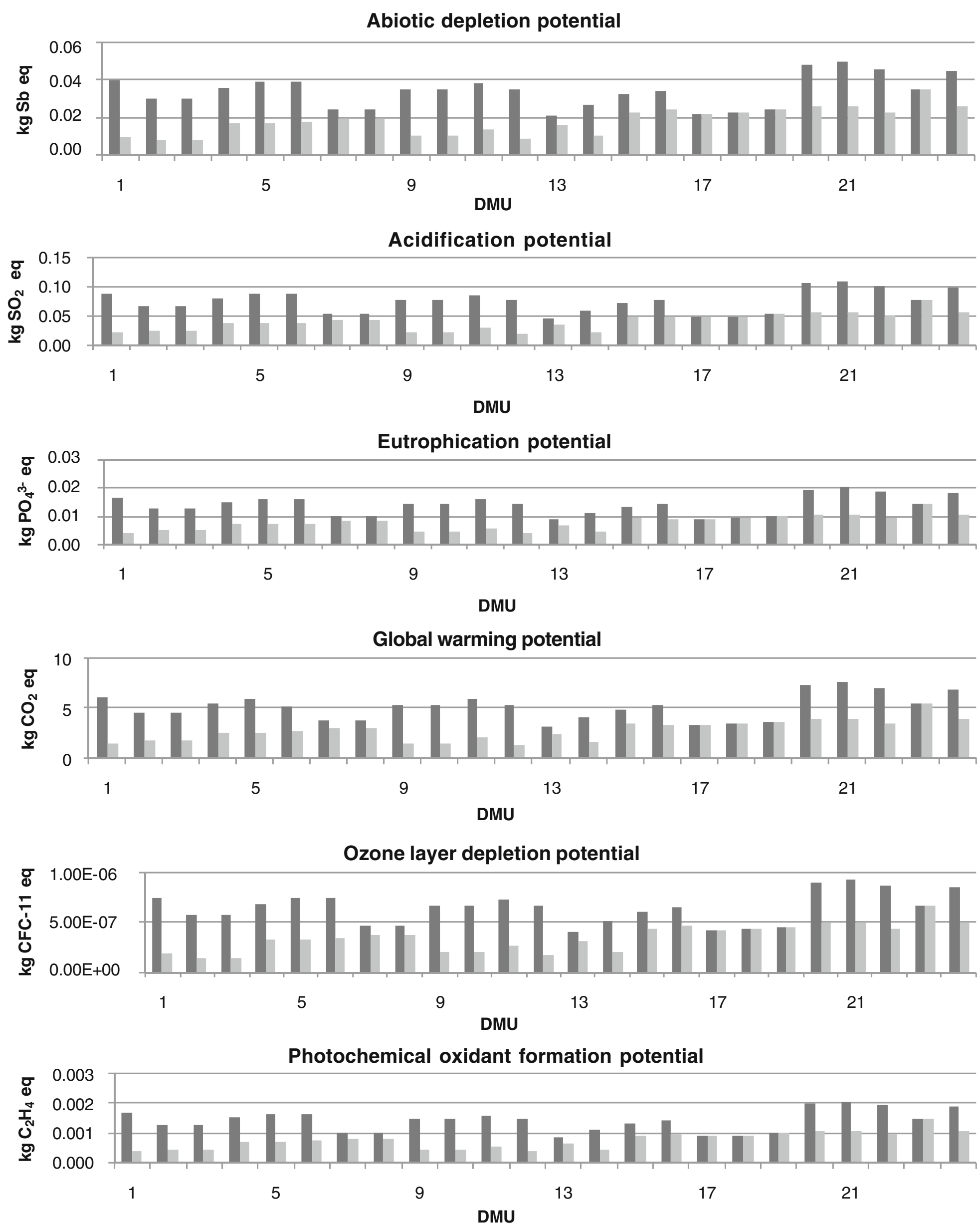


**Fig. 2** Environmental impact potentials of original DMUs (*black bar*) and virtual targets (*gray bar*) per kilogram of output

that the reduction in input consumption was notable with respect to the current values. In this sense, inputs I-3 and I-5 had reductions of up to 60%, while I-6 and I-2 presented reductions below 40%. OBad (discards) presented a 47% reduction with respect to the current figures. DEA estimated these important reductions in resources just resorting to the observed input/output data and extending to every DMU the best practices observed in the sample.

### 4.5 Brief discussion of the case study

The results presented within this methodology achieved the important objective of integrating the environmental impacts of the fleet together with economic issues, such as operational efficiency. In this sense, the results presented in Figs. 2 and 3 show how the link between operational efficiency and environmental impacts is possible by optimizing resource usage (waste reduction, unproductive inputs, or incorrect use of processes) in order to reduce the potential environmental impacts in different impact categories. Therefore, the use of DEA in this methodology introduces operational benchmarking into LCA. However, this methodology does not integrate social issues in LCA studies.

The proposed DEA model for this case study was the SBM-Undesirable Outputs model. This model was chosen for trawling activities due to the fact that trawling fisheries have a great amount of discarded fish (around 40% of total capture for the studied fishery). Even with the inclusion of this bad output, the environmental impacts generated by discards still cannot be assessed, but it proved a feasible and suitable method for quantifying the potential improvements in fish discarding. For other fishery and gear case studies, the convenience of using the SBM-Undesirable Outputs model should be assessed regarding the significance of discards. For some gears that have very small amounts of discarding, such as creels or purse seiners, a regular SBM model would be sufficient.

## 5 Perspectives and conclusions

Given the need to inventory a representative number of vessels to conduct a fishery LCA, the proposed LCA+DEA method arises as a general methodology for fisheries. Consequently, the proposed LCA+DEA method should become a common practice in LCA case studies for fisheries. Nevertheless, among the perspectives for this five-step method, its potential application to other facilities such as farms or wastewater treatment plants is considered. Actually, whenever LCI data for multiple similar facilities are available, the proposed method can be applied just following the five steps detailed in Section 3.1.

The new methodological approach for fisheries proved to entail appealing characteristics, among which, the following are highlighted:

– Avoidance of the use of average inventories when assessing a high number of similar facilities. In this sense, undesirable standard deviations are prevented.
– Facilitation and enrichment of the interpretation of the results for multiple LCAs. The LCA+DEA method is not limited to environmental impacts but adds an economic dimension to the sustainability assessment of fisheries by integrating an operational benchmarking of the vessels' performance.
– Means for eco-efficiency verification. The LCA+DEA approach reveals the link between operational efficiency and environmental impacts, quantifying the environmental consequences of operational inefficiencies. The application of LCA to the virtual targets quantita-

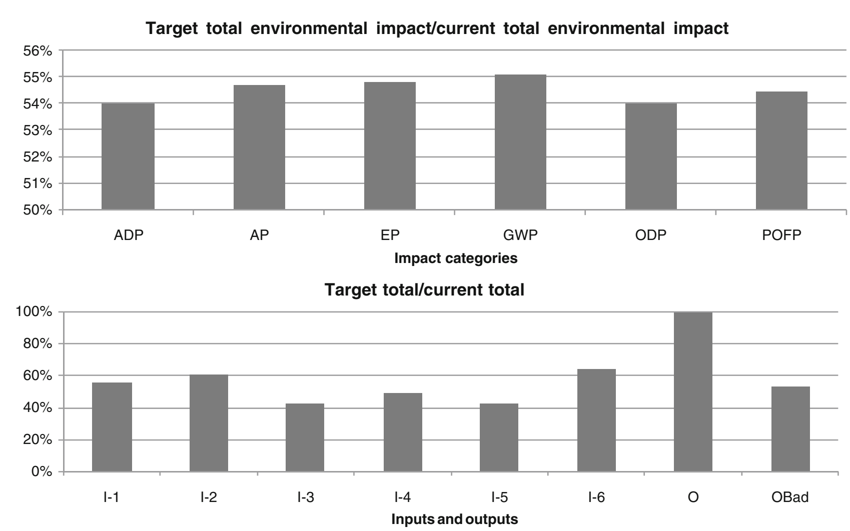


**Fig. 3** Target versus current total inputs consumption and environmental impacts for the fleet as a whole

tively verifies whether the operational benchmarking leads to a better environmental performance.

– As shown for the trawling case study, in those cases where impact categories are not yet established or are out of consensus, the complementary use of DEA enables the quantification of potential improvements for controversial issues such as fish discarding. This advantage is possible due to the availability of a wide range of DEA models. Examples of specific models with interesting potentials of use include, among others, weighted models and OBad models.

The underlying philosophy for the LCA+DEA method is to join the strengths and minimize the weaknesses attributable to both methodologies so that a synergistic effect is achieved by maintaining a quantitative character. Therefore, the final recommendation is to adopt this LCA+DEA approach as the regular methodology for the LCA of fisheries.

**Acknowledgments** D. Iribarren wishes to thank the Spanish Ministry of Education for financial support (grant reference: AP2006-03904). The authors would like to thank all the anonymous skippers and sailors who kindly agreed to answer the questions proposed in the questionnaires, as well as the anonymous reviewers for their constructive comments and suggestions.

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